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Original scientific paper

WAVELET-BASED AUDIO FEATURES OF DC MOTOR SOUND*

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Abstract. *The usage of wavelets is widespread in many fields nowadays, especially in signal processing. Their nature provides some advantages in comparison to the Fourier transform, and therefore many applications rely on wavelets rather than on other methods. The decomposition of wavelets into detail and approximation coefficients is one of the methods to extract representative audio features. They can be used in signal analysis and further classification. This paper investigates the usage of various wavelet families in the wavelet decomposition to extract audio features of direct current (DC) motor sounds recorded in the production environment. The purpose of feature representation and analysis is the detection of DC motor failures in motor production. The effects of applying different wavelet families and parameters in the decomposition process are studied using sounds of more than 60 motors. Time and frequency analysis is also done for the tested DC motor sounds.*

Key words: *wavelets, detail coefficients, approximation coefficients, audio features, DC motors*

1. INTRODUCTION

Wavelets can be used for different purposes, including de-noising, signal parameterization and analysis [1]. Among other methods, wavelets are proposed to overcome certain limitations of the Fourier transform, especially when the time domain resolution is in focus [2-4]. Roots of wavelet method date back to 1909 when Alfred Haar proposed wavelets as an alternative method to Fourier transform, although Fourier himself had mentioned wavelets as a mathematical model in his papers earlier [3]. During the century, particularly in the last few decades, scientists developed wavelet families for various applications. These families are often named by the scientists: Gabor, Morlet, Daubechies, Haar, Meyer, etc. However,

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there are others named by their shape or mathematical model: Mexican hat, biorthogonal, reverse biorthogonal, etc [2,3].

Lots of studies have shown that wavelets can be used in different areas. Most common applications of wavelets are present in signal processing, usually when de-noising of signals such as audio signals, images, special acoustical signals (for example room impulse responses) and biomedical signals (electromyogram, electrocardiograph and electroencephalogram) is in focus [2-6]. The usage of wavelets is widespread, not only for noise removal. Remote sensing of very low-frequency signals and estimation of truncation time of a room impulse response are also applications where wavelets have found their place [7,8].

Recently, increased interest in both academia and industry has been shown for audio signal classification, audio event detection and auditory scene recognition. This kind of audio signal processing plays a vital role in biomedical engineering, mechanical engineering, telecommunications, acoustics, etc. In that regard, different features of audio signals are extracted and used for classification, detection and recognition purpose [9,10]. Some of those features are based on wavelets [11,12]. Although they are not frequently used, their potentials are quite perspective as they can provide good results in artificial intelligence based automated classification for particular applications such as industrial monitoring [10,13] or musical acoustics [12].

One of the significant problems always present in the industry is how to assess the quality of a product (e.g., produced motors) or how to detect a faulty product (motor) and recognize the failure type. Several different approaches are already presented [13]. Unfortunately, there is no established optimum approach. The one attracting significant attention lately is based on usage of sound generated by the tested product. On the other hand, thanks to recent development in audio signal processing and artificial intelligence, advanced machine/deep learning-based methods have become available options in product quality assessment. Here, since every product has its specific sound characteristics, a logical solution would be to apply a customized set of audio features and classification algorithm appropriate for that particular use-case.

The literature shows that signal decomposition into detail and approximation coefficients can be used for feature extraction, especially when audio signals and images are in focus [9,14]. This paper presents the study's results using wavelet decomposition into detail and approximation coefficients as audio features for a classification purpose. Sounds of more than 60 recorded DC motors, faulty and non-faulty ones, are analyzed by applying the wavelet decomposition. Since there are several parameters of wavelets, the effects of changing these parameters on a set of audio features consisting of detail and approximation coefficients are investigated. Besides, the possibilities of using statistics of the extracted wavelet-based audio features consisting of absolute and mean values as well as standard deviation are observed, too. The goal is to define a procedure and relevant audio features capable of making a distinction between sounds of faulty and non-faulty motors. In that regard, the frequency analysis of motor sounds is also done for a better understanding of signal nature and results. The processing is done in Matlab software package, and representative examples are presented here.

The paper is organized in five sections including introduction and conclusion. Section 2 provides relevant background information. Section 3 presents the methodology of this research step by step. Section 4 gives the results of analysis of wavelet-based features extracted from DC motor sounds. The paper is concluded in section 5 with suggestions for future work.

2. RELATED WORK

Techniques used for detection of failures (faults) in motors include vibration monitoring (vibration signature), motor current signature analysis (MCSA), electromagnetic field monitoring, chemical analysis, temperature measurement, infrared measurement, acoustic noise analysis (sound signature), and partial discharge measurement [15]. Among these, current signature, vibration signature and sound signature analysis are the most common in use [16]. MCSA is a rather popular and reliable technique providing good results, although in some cases, it is not sensitive enough because of the low signal-to-noise ratio. It also has spectral leakage and low-frequency resolution as well as the installation can be complicated [16]. Vibration analysis requires appropriate sensors (accelerometers), which can be an additional expense, and sometimes it is not easy to correctly place the sensor in the right position. The latter is especially valid in industrial environment where dust, moisture and high temperature is often present [15,16]. Sound analysis is contactless, low-cost and easy installation approach, where problem typically comes from the noise of the industrial environment. MCSA is often used in combination with sound signature analysis [16,17]. These techniques, particularly sound signature analysis, are used in analyzing and detection of rotor faults, bearing faults and unbalanced faults in wings [15].

The development and popularity of machine/deep learning techniques have led to their usage in various areas, including fault detection in different types of motors [18]. Here, they can be considered an upgrade of the traditional techniques able to give better results and more advanced functionalities. Machine/deep learning techniques include well-known algorithms like support vector machine, K-nearest neighbors (KNN), neural networks, cross-validation, etc. [18-20]. Different types of KNN algorithms like fine KNN, weighted KNN and subspace KNN can provide classification accuracy close to 100 % for all motor faults tested in Ref. 21. It is worth mentioning that machine learning requires an adequate set of features to be provided at the input [19,20].

Different methods can be applied for feature extraction, and different features can be used for audio signal parameterization [18,19,21]. Features are typically divided into categories such as time domain features (e.g., zero-crossing rate), frequency domain features (e.g., fundamental frequency and spectral peaks) or perceptual domain features (e.g., loudness, sharpness and roughness) [10]. There are some recent studies where wavelet-based features are applied for motor faults detection and motor classification [11,12,17,22]. An example is [22], where experimental results prove that wavelets can be used for this purpose as simple, easy and fast method.

Audio signals can be decomposed by the wavelet transform into detail and approximation coefficients considered as wavelet-based features. Typically, the pre-processing stage precedes the wavelet transform. In this stage, audio signals are divided into smaller segments (short-term frames) with certain overlap, although in literature, it can be found that wavelet transform is also implemented on longer (mid-term) frames or whole signals [11,17,22]. Considering all three cases, the feature extraction results depend on many factors, including the type and size of the recorded signal. For longer signals, segmentation is necessary, while for shorter signals, segmentation can sometimes be skipped [22]. Frame size can vary, but it is important to emphasize that shorter frames can provide better classification results. Also, it is important to mention an overlap of frames, where in most cases, it is 50% of frame size [23], although it could even be 75% [22], while some authors do segmentation without any overlap [11,17].

As audio signals usually contain noise, de-noising in pre-processing can often be beneficial. De-noising can be done by applying wavelets, notch filtering, moving average filtering, etc. [11,17].

One of the steps in feature processing can be calculating the statistical values of the obtained detail and approximation coefficients. Since it has been shown that coefficient's negative values can cause errors in classification [17], an alternative can be to work with their absolute values. The coefficient statistics also includes the mean of absolute values, standard deviation and ratio of absolute mean values providing additional information about features [9,24,25].

Regarding the application of wavelets for fault analysis in different types of motors, the most common wavelets are Haar and Daubechies, although Coiflets, Symlet and Meyer wavelets are also proposed for that purpose [11,17]. The selection of adequate wavelet type is not an easy task, especially in some cases. For example, certain wavelet families, like Daubechies, have a large number of different functions (there are up to 45 Daubechies wavelet functions when Matlab is used). In [12], authors present their research about the choice of right wavelets for the classification of percussive sounds. Besides the selection of appropriate audio features, it is also important to choose the right classifier. Similar to the situation with features, different classifiers are proposed and used in studies [15-17].

For the majority of authors, the level of decomposition in the wavelet transform is one of the most important parameters whose effects need to be investigated. As decomposition level increases, loss of resolution can be a major problem in the obtained coefficients [12,26]. For example, the first level coefficients extract the finest resolution. Some authors use the decomposition up to level 8 or 9 [11-13], while some other authors have a standpoint that suitable results can be obtained using much lower levels, for example, 3, 4 or 5 [15,26].

3. Methods of Analysis

More than 60 DC motors are included in the analysis. Some of the important characteristics of these motors are: input voltage from 12 V to 13 V, no load speed (rotation per minute) about 80, maximum output power from 18 W to 25 W, approximate dimensions $16 \times 13.5 \times 4.5$ cm. The sound of each motor was recorded in an anechoic boot located in the production hall of the motor manufacturer. The anechoic boot has a "box in a box" construction. The outer box is a semi-anechoic chamber (only the floor is reflective) representing a working place of an operator performing the measurements. The inner box is a small sound insulated boot of approximate volume of 0.5 m^3. The ambient noise outside the anechoic boot is generally rather high, since it is mainly generated by machinery located in the production hall. However, since the measurements were done during weekends when only a minority of machines was active, the ambient noise inside the inner boot was significant only at low frequencies, mainly below 300 Hz.

The motors were placed on a test bench provided by the motor manufacturer, see Fig. 1. This test bench was able to drive the motors with adequate force and to apply an adequate load simulating real conditions. The motors were driven in two directions of rotation, where operation in each direction lasted approximately 8 s. The measuring microphone was placed about 40 cm from the tested motor.

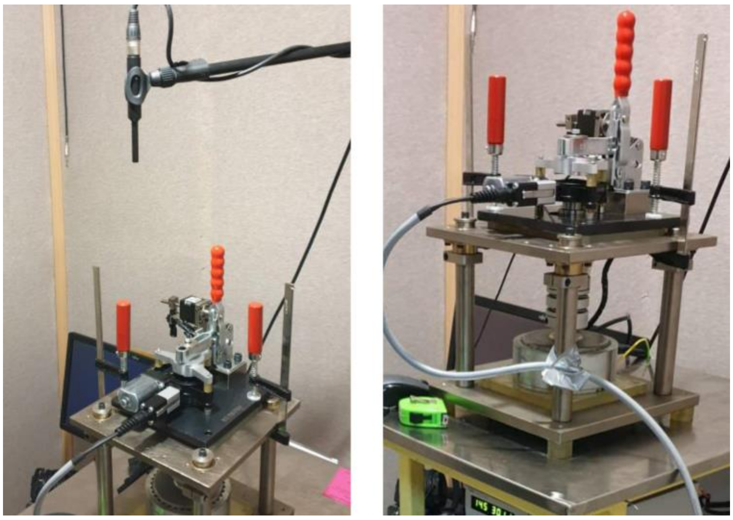

Fig. 1 Test bench driving the motors with adequate force and applying adequate load

Pre-processing here is related to the extraction of relevant parts of the recorded audio signals and segmentation when it is required. In order not to use the transition regions in the beginning and at the end of the signals, their medium parts of a duration of 5 s for each direction of rotation are extracted and further processed. The wavelet-based features are extracted either from the whole signals or from signals divided into segments. According to literature, the size of segments (frames) and overlap between them can vary from one study to another. The signals are here segmented in short-term frames of 50 ms with an overlap of 50%, that is, 25 ms.

The starting point in the analysis is to observe the DC motor sounds in time and frequency domain in order to notice specific sound properties, and, if possible, make a distinction between motors with certain faults (faulty motors) and motors with good characteristics (non-faulty motors). Since these motors are brand new ones, it is expected that there will be only tiny differences among their sounds in most cases. The exceptions are expected to be seen only in rare cases of serious failures. Separation between non-faulty and faulty motors is done by the experienced personnel of the motor manufacturer. The most common faults found in these motors are commutator faults, mechanical unbalance, bearing and gearbox defects.

Wavelet-based feature extraction starts with the decomposition of an audio signal. The decomposition is usually done using discrete wavelet transform (DWT) rather than continuous wavelet transform (CWT) because of its easier implementation in multilevel signal decomposition [3-5]. Every signal is decomposed into detail and approximation coefficients (high and low-frequency components) at each level [3-6]. This is why the DWT is equivalent to low and high pass filtering [4]. Fig. 2 presents the whole process of decomposition down to level 3, where LP is a low-pass filter, HP is a high-pass filter, Ax stands for approximation coefficients at decomposition level x, Dx stands for detail coefficients at decomposition level x, and 2↓ is down-sampling.

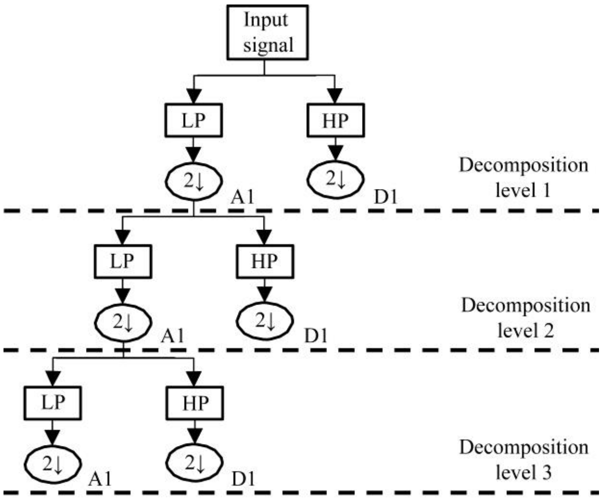

Fig. 2 Block diagram of wavelet transform decomposition into detail and approximation coefficients

Different wavelets are applied to the pre-processed signals to provide an adequate set of wavelet-based features being able to make a difference between faulty and non-faulty motors. Generally speaking, the most common wavelet used in audio signal processing is the Haar wavelet. This wavelet is proved to be the most stable in signal de-noising, although Daubechies wavelets provide somewhat better results than Haar in this particular application [5]. Other wavelet families used here are: Coiflets, Symlet, biorthogonal, reverse biorthogonal and discrete Meyer.

Investigation of the effects of wavelet decomposition level is an important part of the analysis, too, especially because many authors use different values for this parameter. Here, the levels of decomposition from 1 to 8 are used.

When the wavelet decomposition is applied to the whole pre-processed signals, absolute values of the obtained detail and approximation coefficients at each decomposition level are treated as wavelet-based features. On the other hand, when the wavelet decomposition is applied to the segmented signals, the mean and standard deviation of the coefficients as well as of absolute values of the coefficients obtained from the segments are considered to be the wavelet-based features.

Apart from the analysis of the recorded signals in time and frequency domain, their wavelet-based features are analyzed in detail, too. Special attention is paid to differences between faulty and non-faulty motors in any of these domains, and to the correlation between the results in different domains (if any). In order to quantitatively evaluate the performance of the wavelet-based features in making a distinction between the motors, a measure named feature difference is calculated as the mean value of differences between the features for non-faulty and faulty motor from all segments normalized by the mean feature value.

The processing described is done in Matlab software package. The fully automated software application is created. The selected wavelets and level of decomposition are applied to the defined signals using the command *wavedec*. The detail and approximation coefficients are generated utilizing two commands - *appcoef* and *detcoef*, respectively, according to the level of decomposition. Other used supporting functions belong to the standard ones for Matlab software. A block diagram of the whole processing including analysis in time and frequency domain as well as wavelet-based feature extraction and quantification is shown in Fig. 3.

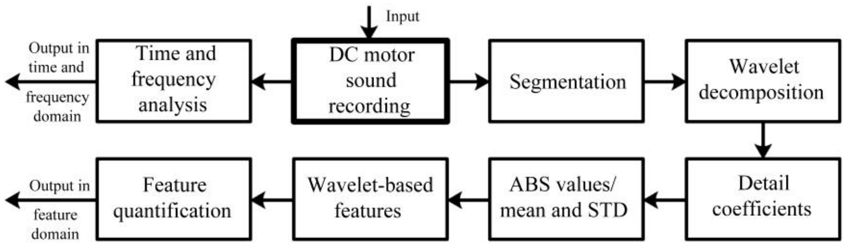

Fig. 3 Block diagram of the processing applied in the time, frequency and feature domain

4. RESULTS

Although more than 60 motors are used in the analysis, only the representative cases are included here illustrating typical behavior of these motors regarding the analyzed issues. The investigation results obtained by applying the wavelet decomposition to the whole pre-processed signals are given first. They are followed by the results obtained from the segmented pre-processed signals. These two approaches in applying the wavelets for audio feature extraction are compared afterward.

4.1. Analysis of full-length signals

The whole (full-length) pre-processed sounds of the duration of 5 s of both faulty and non-faulty DC motors in one direction of rotation in the time domain are given in Fig. 4 (a). Results show that there are certain fluctuations of amplitude (levels) in time. In some cases (signals), these amplitude fluctuations are more prominent. The fluctuations can have a shape similar to a low-frequency pattern, or some sudden onset of high amplitude can appear in particular time moments. However, it is rather difficult to distinguish between non-faulty and faulty motors considering only the signals in the time domain.

By analyzing the spectra of the signals shown in Fig. 4 (b), it can be seen that there are some prominent low-frequency components (below 100 Hz) mainly caused by the ambient noise. In the remainder of the frequency range, some peaks and dips appear. One more observation (not shown here) is that distinction between directions of rotation can be made in an easier way in the spectral domain than in the time domain. However, even in the spectral domain, it is not easy to differentiate the faulty motors from the non-faulty motors. In that regard, it would be very beneficial to find an alternative approach/domain able to make a clearer distinction between these motors.

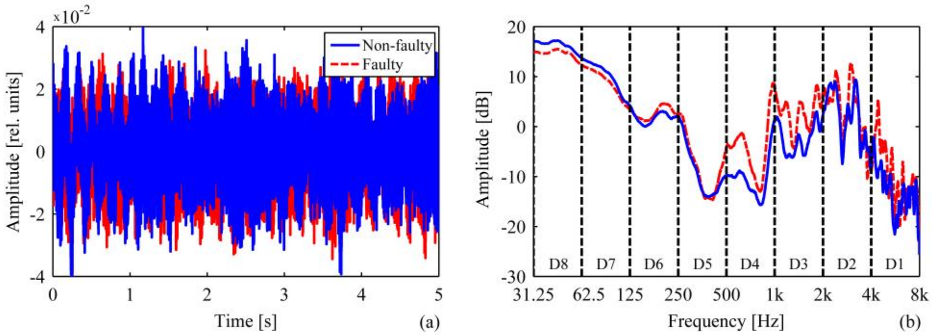

Fig. 4 Pre-processed sound signals of non-faulty (blue) and faulty (red) DC motors for the direction of rotation 1: (a) time domain, (b) frequency domain

When the wavelets are applied to the full-length pre-processed signals, the results are the detail and approximation coefficients of these particular signals. The decomposition process using Daubechies 2 wavelet (db2 in Matlab) and decomposition levels from 1 to 8 is illustrated in Fig. 5, where absolute values of the detail coefficients for the sound of a non-faulty and faulty DC motor are shown.

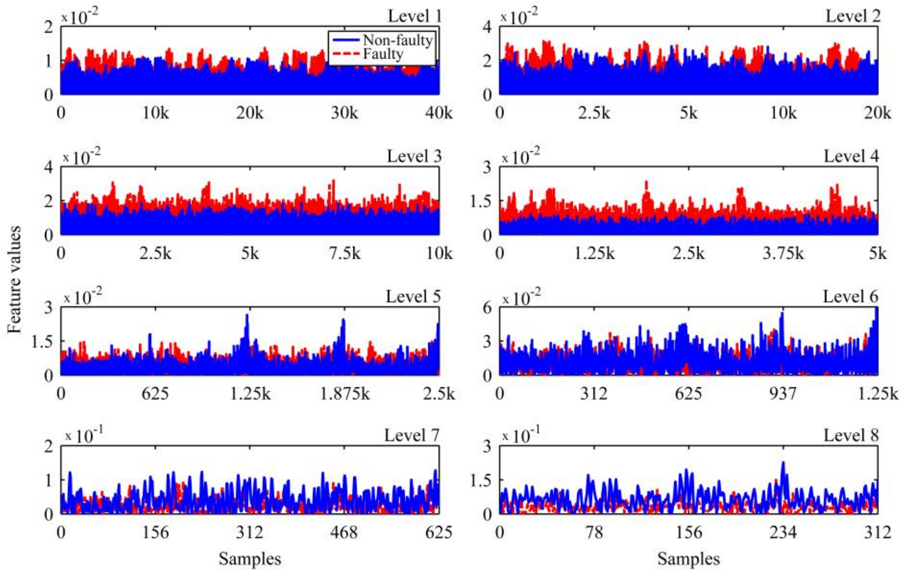

Fig. 5 Detail wavelet coefficients after applying Daubechies 2 wavelet to full-length signals (with taking coefficient absolute value) for non-faulty (blue) and faulty motor (red) for the direction of rotation 1, and using the decomposition levels from 1 to 8

The detail coefficients for the majority of decomposition levels are rather similar for the non-faulty and faulty motor. This is valid for the levels 1 and 2 as well as for the levels from 5 to 8. However, the coefficients for the decomposition levels 3 and 4 show some differences, since the values of detail coefficients for the faulty motor are greater than those for the non-faulty motor. The noticed difference between non-faulty and faulty motor represents a promising result that will be explored in more detail later. From a general point of view, it is worth noting that the length of detail coefficient array becomes shorter with the increase of the decomposition level, which is an inherent property of the wavelet decomposition.

The results for detail coefficients obtained using different decomposition levels could have a certain correlation with the signal representation in the frequency domain, that is, the signal spectrum. All measured signals are sampled at 16 kHz, so the maximum frequency of the signals is 8 kHz. As described above (see Fig. 2), the decomposition starts at level 1, where the signal is passed through a high pass and low pass filter yielding the detail and approximation coefficients at the decomposition level 1, respectively [27]. These coefficients are then down sampled by 2, and the procedure is repeated until the final decomposition level is reached. In this manner, the signal frequency range is divided into two equal parts (related to detail and approximation coefficients) at every level of decomposition.

Following the described procedure, the frequency range up to 8 kHz is first divided into upper part (from 4 kHz to 8 kHz related to the detail coefficients at the decomposition level 1) and the lower part that is further divided at the next decomposition level. In that respect, the frequency content from 4 kHz to 8 kHz is somehow correlated with the detail coefficients at the decomposition level 1 (D1). What is worth emphasizing is that the detail coefficients represent the wavelet filtered data in time, while the spectrum is a spectral representation of the signal calculated from the whole time interval used for the analysis. As the decomposition goes through the next decomposition levels, up to level 8, the frequency range related to the detail coefficients at every next level is halved. Thus, the frequency ranges after halving become: from 2 kHz to 4 kHz at the decomposition level 2, from 1 kHz to 2 kHz at the decomposition level 3, etc. The lower part of the frequency range at the last decomposition level is related to the approximation coefficients, and in the presented case it is from DC to 31.25 Hz. This procedure is illustrated in Fig. 4 (b) by vertical lines and symbols D1 to D8.

4.2. Decomposition of segmented signals

Most authors have reported that segmenting the signals into frames might improve the results in the feature extraction using wavelets [11,17,23]. When a single frame is observed, the decomposition using wavelets is done in the same way as in the case of full-length signals. Every frame is decomposed using a particular wavelet (Daubechies 2 in this case) up to level 8. However, opposite to the case when the full-length signal is decomposed, here the feature vectors consisting of the mean values and standard deviations of detail coefficients represented by their absolute values have the same length independently of the decomposition level, see Fig. 6. The same sounds are used for both figures 5 and 6.

In a similar manner as in Fig. 5, the most prominent differences between the non-faulty and faulty motors exist at the decomposition levels 3 and 4. As mentioned above, these results are consistent with those from the frequency domain, where the biggest differences are present in the range from 1 kHz to 2 kHz and from 500 Hz to 1 kHz, see Fig. 4 (b), related to the decomposition levels 3 and 4. Comparing the features obtained using mean values, Fig. 6 (a), and standard deviation, Fig. 6 (b), they both lead to certain differences between the non-faulty and faulty motors, although the mean values provide more stable results. In that regard, both procedures (mean value based and standard deviation based) can be used for feature extraction.

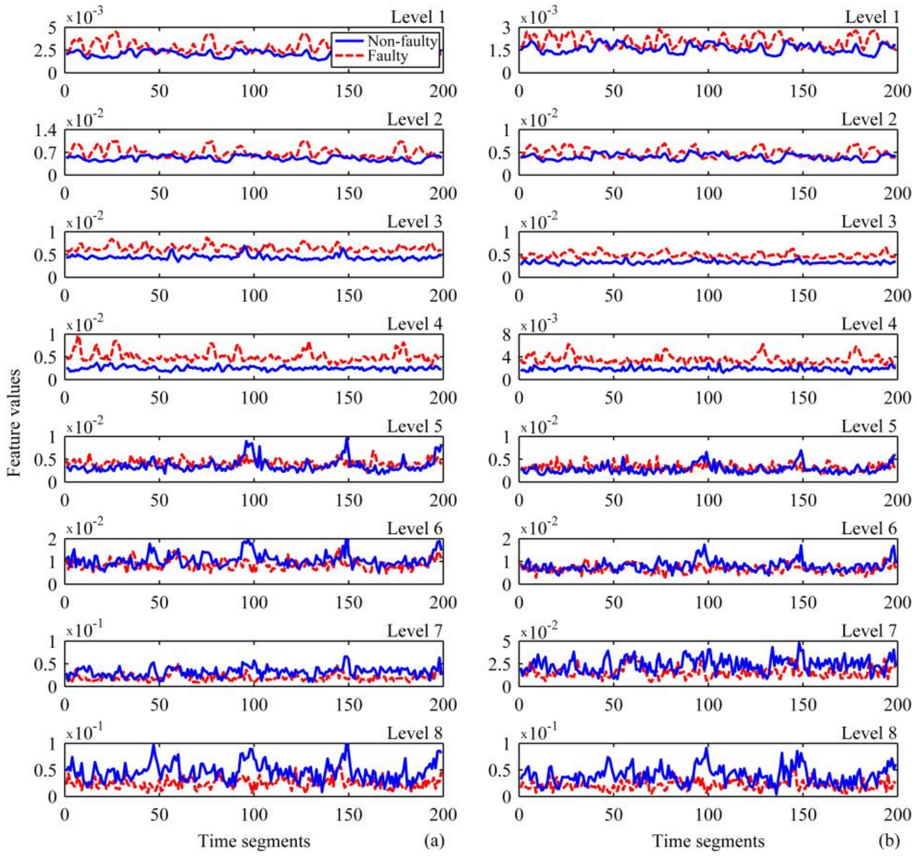

Fig. 6 Detail coefficients after applying Daubechies 2 wavelet to segmented signals (with taking coefficient absolute value) of non-faulty (blue) and faulty motors (red) up to level 8 of decomposition: (a) mean values, (b) standard deviation

To show the extent to which the proposed features vary in the case of the non-faulty motors in reference to the faulty motors, the detail coefficients at the decomposition level 4 of eleven non-faulty motors and one faulty motor are presented in Fig. 7. The detail coefficient mean values for the non-faulty motors are concentrated in a rather narrow region having smaller feature values than the faulty motor. Thus, there is a prominent difference between the non-faulty and faulty motors.

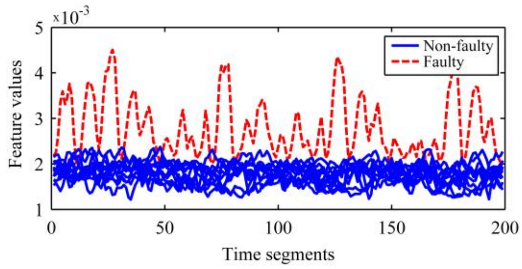

Fig. 7 Mean values of detail coefficients after applying Daubechies 2 wavelet to segmented signals (with taking coefficient absolute value) of eleven non-faulty motors (blue) and one faulty motor (red) at decomposition level 4

As done in the previous research of the authors of this paper (see [1]), mean values and standard deviation of the detail coefficients without applying absolute value are also used for feature extraction in some other papers as well [1,13,22]. The wavelet-based features (detail coefficients) obtained in this way using the same sounds from figures 5 and 6 are shown in Fig. 8. However, these results are not as good as those presented in Fig. 6. The procedure employing mean values (but without taking the absolute value of detail coefficients) provides almost no difference between non-faulty and faulty motors. On the other hand, the procedure employing standard deviation without absolute value can result in certain, but rather small difference between compared motors, as shown in Fig. 8 (b). The mentioned observations are logical since detail coefficients are bipolar having a mean value close to zero, while standard deviation is calculated using the square function, eliminating the bipolarity. This trend of having worse results without absolute value than with absolute value appears in almost all analyzed DC motors. This is why the procedure without absolute value will no longer be considered during this research.

4.3. Effects of changing the wavelet function

When the wavelet function is changed from Daubechies 2 to other functions (Haar, Symlet, Coiflet, biorthogonal, reverse biorthogonal, Meyer), the patterns of detail and approximation coefficients are also changed to a certain extent. Fig. 9 illustrates four cases of usage of different wavelet functions (Haar, Simlet 8, Coiflet 5 and discrete Meyer) applied to the segmented signals of non-faulty and faulty DC motors. Only the wavelet-based features for the first four decomposition levels obtained using absolute and mean values of the detail coefficients are shown. Haar wavelet proved to be the most stable one in the previous research [5,8], but differences between non-faulty and faulty motors obtained with Haar wavelet, in this case, are smaller than those obtained using Daubechies 2. The other three wavelets provide rather similar results like the ones presented in Fig. 6.

The described observations are quantitatively supported by the measure feature difference calculated as explained in section 3. For the decomposition level 4, the wavelets whose results are shown in Fig. 9 lead to the following values of the feature difference: Daubechies 2 leads to the feature difference of 0.68, Symlet 8 to 0.72, Coiflet 5 to 0.69 and discrete Meyer to 0.75, while Haar wavelet leads to the difference of 0.37. These results for feature differences confirm that Haar wavelet provides smaller difference between non-faulty and faulty motors than Daubechies 2 wavelet or any other used here.

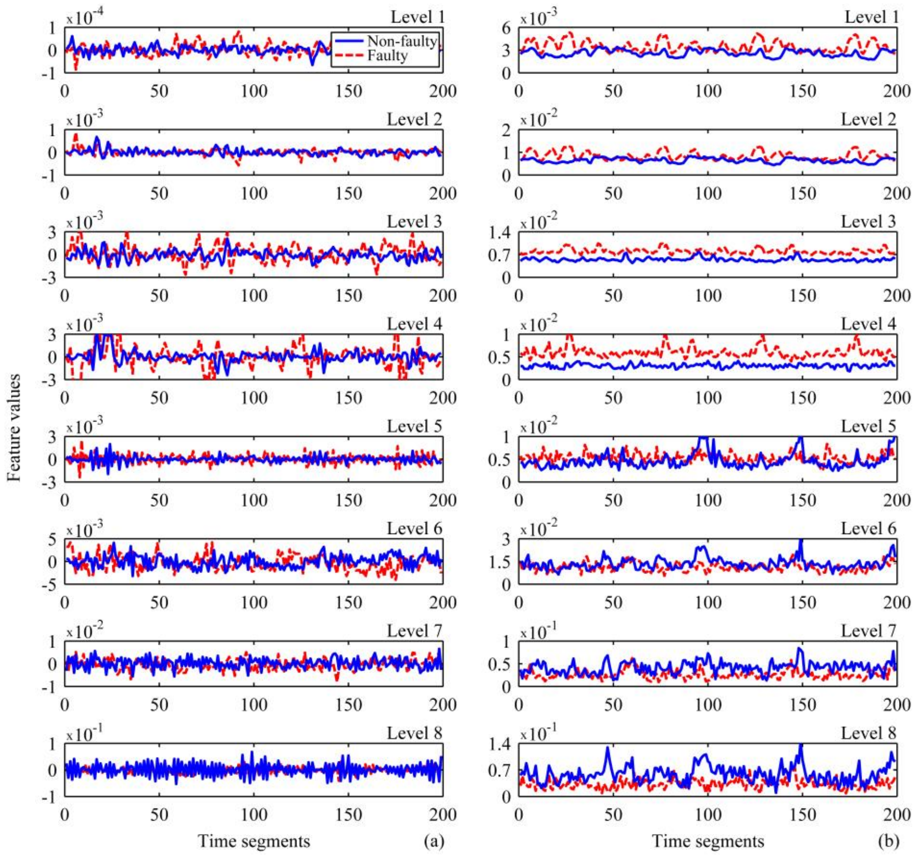

Fig. 8 Detail coefficients after applying Daubechies 2 wavelet to segmented signals (without taking coefficient absolute value) of non-faulty (blue) and faulty motors (red) up to level 8 of decomposition: (a) mean values, (b) standard deviation

4.4. Differences between motors in detail coefficients and spectra

From the analysis of detail coefficients and time/frequency characteristics of sounds of all used DC motors, two specific cases of correlation of results from different domains stand out. The first case (case 1) is similar to the one given in figures 5, 6 and 9, where there are certain differences between non-faulty and faulty motors in both detail coefficients and spectra. Here, the differences in detail coefficients at a particular decomposition level are related to the differences in spectra in a particular frequency range, as explained in Section 4.1, see Fig. 4 (b). The second case (case 2) is opposite to the first one. In this case, there are almost no differences in the detail coefficients and spectra between the non-faulty and faulty motors. Again, the differences in the detail coefficients at a particular decomposition level are compared to the differences in spectra in a particular frequency range. These cases are presented in more detail below.

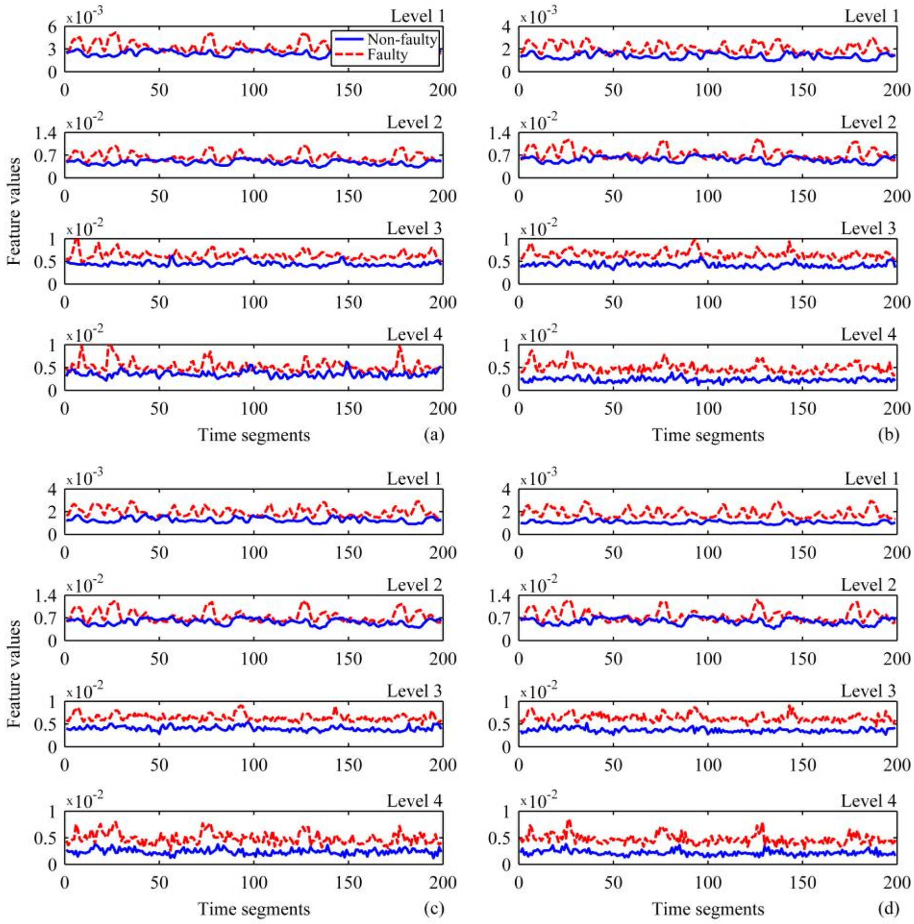

Fig. 9 Detail coefficients given as mean values from the frames after applying (a) Haar, (b) Symlet 8, (c) Coiflet 5 and (d) discrete Meyer wavelets to segmented signals of non-faulty (blue) and faulty motors (red) up to level 4

In order to shed light from one more perspective, another example of a certain correlation of differences between non-faulty and faulty motors in the detail coefficients and spectra is shown in Fig. 10.

The processing is identical to the previously described one. Daubechies 2 wavelet up to the decomposition level 8 is applied to the pre-processed signals of non-faulty and faulty motors. Wavelet-based features consist of mean value and standard deviation of the absolute value of the detail coefficients from every frame. Differences between the non-faulty and faulty motors are the most prominent in the detail coefficients from the decomposition level 1 up to level 4. Also, there are some smaller differences present at level 5. Similar results are found in the spectra of the analyzed signals, see Fig. 9 (c). An exception is found in the region/coefficients D6, where a bigger difference exists in the spectra than in the detail coefficients.

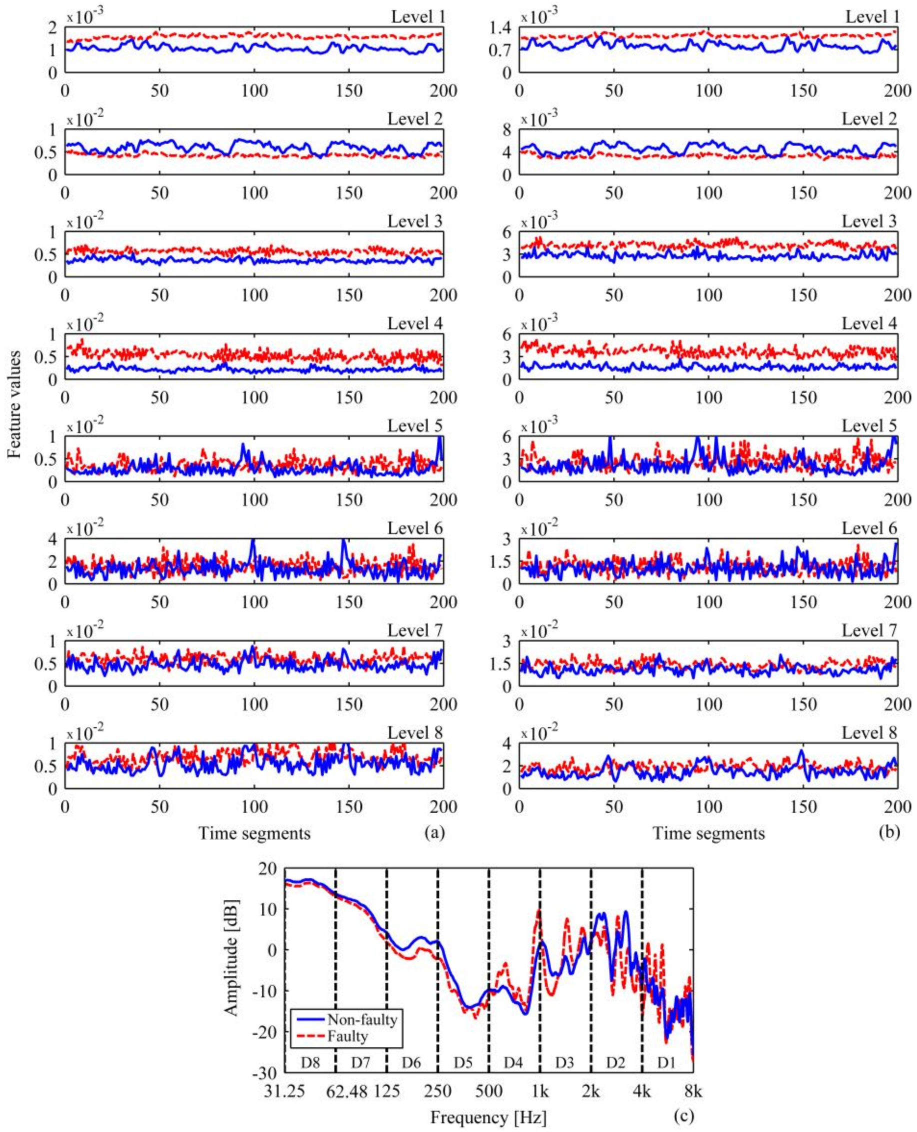

Fig. 10 Detail coefficients after applying Daubechies 2 wavelet to segmented signals (with taking coefficient absolute value) of non-faulty (blue) and faulty motors (red) up to level 8 of decomposition: (a) mean values, (b) standard deviation, (c) spectrum of full-length signals (the case with certain differences between non-faulty and faulty motors)

It should be kept in mind that the motors used in the present research are the new ones coming out from the production line. In that regard, faulty motors make up the minority. Moreover, only very few of those faulty motors have serious failures. The sound of such a motor is distinguishable from the non-faulty ones. However, in many other cases where the fault is a minor one, the sounds of non-faulty and faulty motors are perceptually similar to each other, and their objective characteristics are also similar. This is why making a distinction between non-faulty and faulty motors having only minor failures is a difficult task. Such a case is presented in Fig. 11.

Independently on whether the mean or standard deviation of the detail coefficients from the frames is applied to generate the wavelet-based feature, these features are similar for non-faulty and faulty motor, as shown in Fig. 11 (a) and (b). This is valid for all used decomposition levels (up to level 8). Spectra of these motors are also similar, although not entirely the same, see Fig. 11 (c). As a consequence of the mentioned similarities, in cases like this one, the wavelet-based features will not provide a clear distinction between non-faulty and faulty motors.

The measure feature difference is also calculated for two specific cases investigated in this section, and the results are summarized in Table 1. The feature difference is significantly larger for the case 1 than for the case 2, which is in line with the noticed behavior of the wavelet-based features for these cases. For the case 1, the feature difference has larger values at the levels of decomposition from 1 to 4, confirming the above stated observation.

Table 1 Feature difference calculated for two cases analyzed in this section (case 1 is related to Fig. 10, while case 2 is related to Fig. 11)

Decomposition level	1	2	3	4	5	6	7	8
Feature difference (case 1)	0.39	0.34	0.42	0.83	0.26	0.18	0.23	0.24
Feature difference (case 2)	0.12	0.042	0.1	0.027	0.068	0.051	0.025	0.001

5. Conclusion

The sound generated by a motor having a certain fault can be significantly changed from the sound generated by a non-faulty motor. The extent of difference depends on the fault, but also on the motor itself. The sounds of non-faulty and faulty motors can be compared from the perceptual point of view, but their objective characteristics such as spectra can be compared, too. An approach that can provide additional information is based on the extraction of some features from the signal (sound) and using these features as attributes describing the motor as a sound source and its condition.

Wavelet technique is one of the options to extract useful features when the sound signature analysis is applied for motor quality estimation. The decomposition of an audio signal into detail and approximation coefficients is the main task in this type of wavelet analysis. By using the adequate wavelet parameters, the differences in wavelet coefficients (representing the wavelet-based features) between non-faulty and faulty motors can become prominent. Although differences between the motors might be seen in the spectra, too, the wavelet-based features provide a different insight into this topic. Apart from the fact that wavelet filtering can emphasize these differences between motors, usage of the wavelet-based features is much more convenient for application of automated classification procedures based on machine/deep learning.

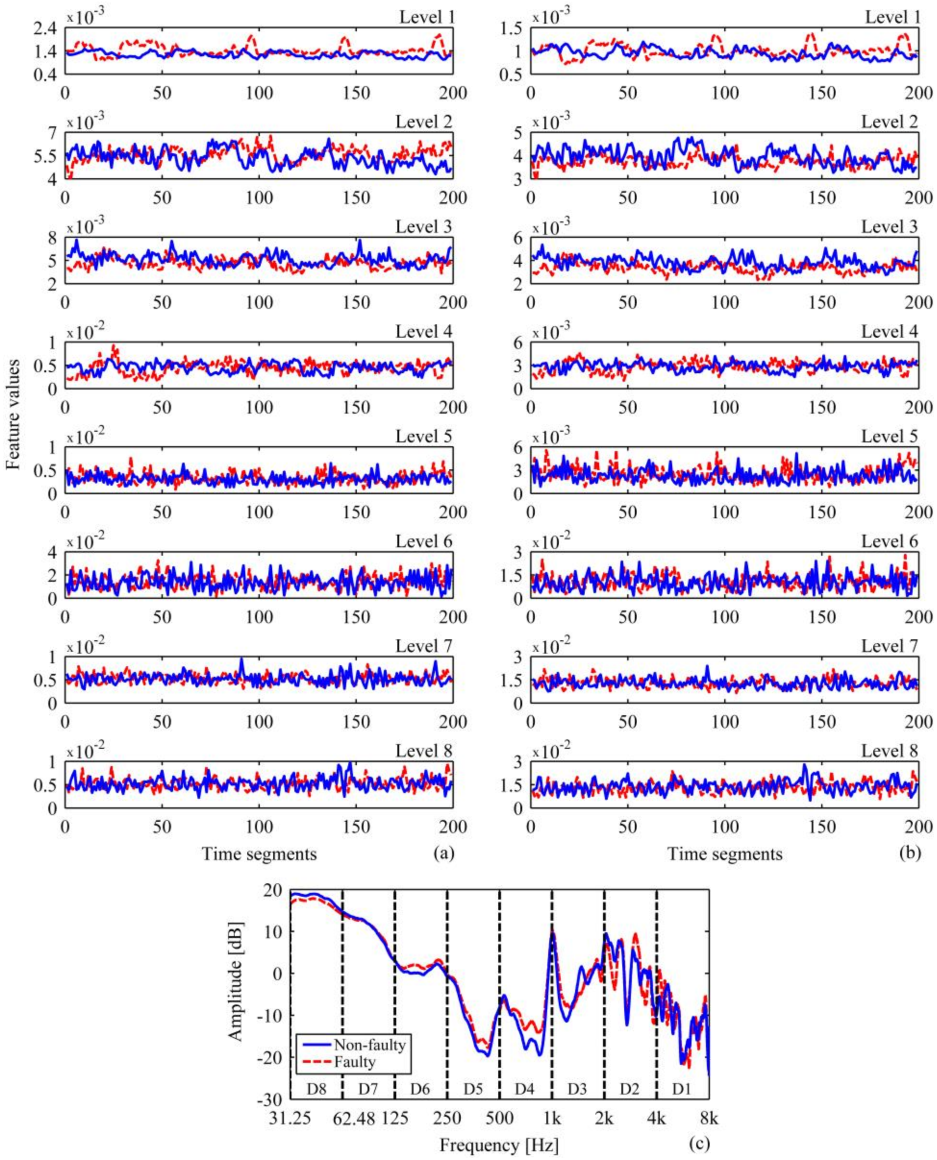

Fig. 11 Detail coefficients after applying Daubechies 2 wavelet to segmented signals (with taking coefficient absolute value) of non-faulty (blue) and faulty motors (red) up to level 8 of decomposition: (a) mean values, (b) standard deviation, (c) spectrum of whole signals (the case without prominent differences between non-faulty and faulty motors)

Regarding the wavelet parameters, it is interesting to note that several different wavelets provide similar results, although there are slightly different cases. For instance, the Haar wavelet does not provide as good results as Daubechies 2 wavelet for this particular application. The present research results show that a few wavelets stand out, including Daubechies, Symlet and Coiflet. The waveform of the Symlet wavelet is similar to that of the Daubechies wavelet, so it is logical that they have a similar impact on the signal decomposition. One of the main observations of this research is that there is no single decomposition level leading to the largest differences between non-faulty and faulty motors. This is use-case dependent. In most cases, there is a correlation between the differences of the motor sound spectra in particular frequency ranges and differences in the wavelet-based features (detail coefficients). Thus, the decomposition level can be chosen according to the frequency range where the largest differences between the compared DC motors occur. In this research, the most prominent differences exist in the upper part of the frequency range, and in the detail coefficients at the levels of decomposition from 1 to 4. Only in rare cases, certain differences between non-faulty and faulty motors can be present in the detail coefficients at the decomposition levels higher than 4.

The sounds of DC motors used in this research were recorded in the production hall of the motor manufacturer, as described above. Future work will also include DC motor sounds recorded in an alternative environment (e.g., the one of different size and ambient conditions). Also, the analysis will be extended to some other cases of correlation of results from different domains in addition to two extreme cases presented here - with and without differences between non-faulty and faulty motors in both detail coefficients and spectra.

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